To what extent does the self-guidance mechanism in TSDiff improve robustness against distribution shifts compa

Assignee Research

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Abstract

Diffusion models have achieved state-of-the-art performance in generative modeling tasks across various domains. Prior works on time series diffusion models have primarily focused on developing conditional models tailored to specific forecasting or imputation tasks. In this work, we explore the potential of task-agnostic, unconditional diffusion models for several time series applications. We propose TSDiff, an unconditionally-trained diffusion model for time series. Our proposed self-guidance mechanism enables conditioning TSDiff for downstream tasks during inference, without requiring auxili

1 Introduction

This paper examines: Predict, Refine, Synthesize: Self-Guiding Diffusion Models for Probabilistic Time Series Forecasting. Research question: To what extent does the self-guidance mechanism in TSDiff improve robustness against distribution shifts compared to conditional diffusion models in cross-domain time series forecasting?.

2 Methodology

Systematic literature search across multiple databases yielded 7 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 5.2/10.

3 Results

7 papers retrieved. 7 claims extracted; 2 independently verified. Quality review score: 5.2/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
TSDiff can generate probabilistic forecasts, including in the presence of missing values.	×	0.05
The implicit probability density learned by TSDiff can be leveraged to refine the predictions of base forecasters.	✓	0.20
The synthetic samples generated by TSDiff are adequate for training downstream forecasters.	×	0.15
Experiments were conducted on eight univariate time series datasets from different domains, available in GluonTS.	×	0.11
The quality of probabilistic forecasts was evaluated using the continuous ranked probability score (CRPS).	×	0.14
The CRPS was approximated by the normalized average quantile loss using 100 sample paths.	×	0.01
TSDiff is competitive against task-specific models on several datasets and across multiple forecasting scenarios, withou	✓	0.15

References

- `http://arxiv.org/abs/2401.03006v2`
- `http://arxiv.org/abs/2110.13179v8`
- `http://arxiv.org/abs/2307.11494v3`